

# optimization

Meaning of optimization:-

↳ minimize or maximize of certain objective function.

Aim of optimization

↳ Find best (optimum) solution for any optimization problem.

→ Examples of optimization Problems / APPs:-

- optimize Parameters of ANN model (weights & bias)
- " Parameters of ANFIS model (Premise & antecedent Parameters)
- Tuning Parameters of PID (get best value of  $K_P$ ,  $K_I$  &  $K_D$ )
- Getting best Placement of WI-FI access point for Indoor Positioning system (IPS)

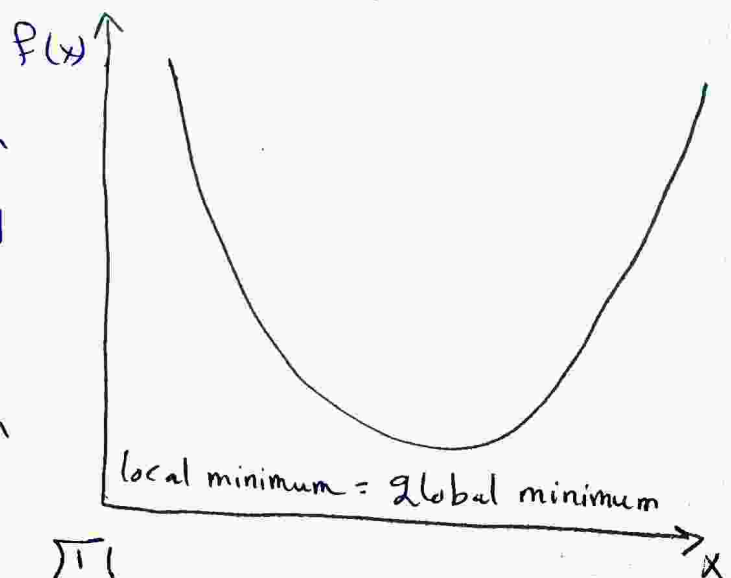
## Notes

local optimum  $\rightarrow$  global optimum

\* Unimodal Function

↳ has single local minimum which is itself the global optimum.

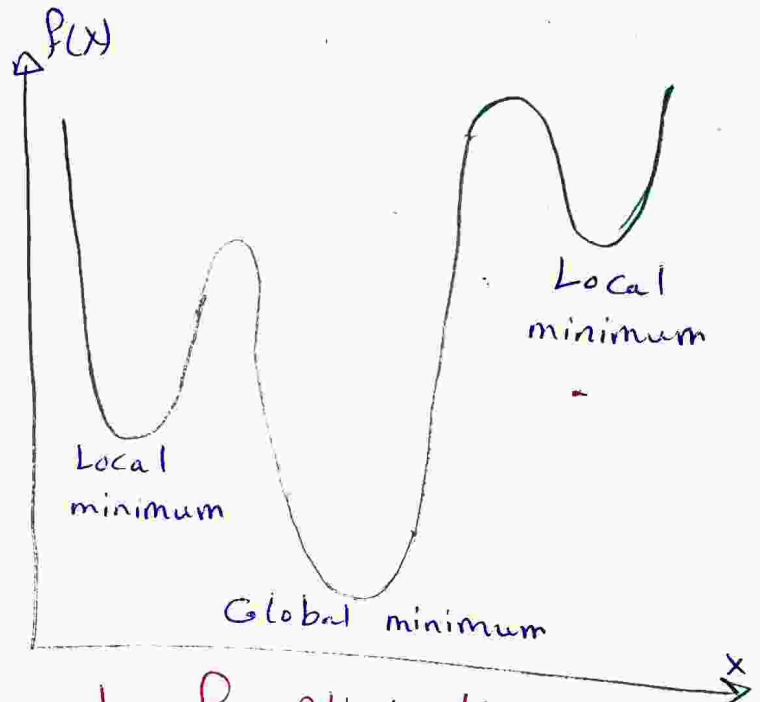
$P(x)$  → objective function to be minimized.



\* The <sup>Global</sup> ~~Local~~ minimum is the least among all local minimum.

## [2] Multimodel Function:-

→ has more than one local optimum and one global optimum ~~function~~



\* What is the ideal target of optimization problem?

↳ It is the global optimum (a good optimization algorithm does not get trapped in any local optimum)

### Basic elements of optimization Problem

1) An objective function  $f$

↳ Function to be optimized (minimized or maximized)

2) The number of components or variables of the objective function that specifies the dimensionality of the optimization problem

$$f(x_1, x_2, \dots, x_D)$$

where  $D$  is no. of variables specifies dimensionality of the problem.

$F(x)$ ,  $x = [x_1, x_2, \dots, x_D]$   $1 \times D$  vector

3) Sets of constraints forced on required solution

↳ most problems constrain at least search domains of the variables vector  $x = [x_1, x_2, \dots, x_D]$

↳ aim of optimization is to find global optimum

$x^* \subseteq R^D$  from allowable search domains, where

$F(x^*)$  has the minimum value in search domain.

### Classification of optimization Problems

classification basis	Types of optimization Problem	
Dimensionality (D)	univariate (D = 1)	Multivariate (D > 1)
Linearity	Linear	Non Linear
Constraints	unConstrained (only <del>the</del> search ranges of $x_d$ are constrained)	Constrained (Additional constraints are forced on $x_d$ )
no. of optimum values	unimodel (one optimum only)	Multimodel
no. of objective	single-objective	Multi-objective (more than one objective to be <del>min</del> optimized)

Separability of Variables $x_d$	Separable Function of $F(x_1, \dots, x_D)$ Can be divided to $D$ Functions in form: $F(x_1) + F(x_2) \dots + F(x_D)$	Non-Separable Can't be divided.
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## Evolutionary optimization Algorithms

(Population-based " " )

↳ Evolutionary optimization algorithms are Population based of candidate solutions, not just one solution.

What is the basic characteristic of Population-based

↳ the iteration policy depends on a Population.

What happens during the iteration?

↳ Population of constant size is maintained, and group of solutions is improved progressively.

Note that "can be neglected"

↳ Having group of solutions "working together" is the key of emulating behavior of biological organisms in modern biology-inspired optimization approaches (e.g. flock of birds, school of fish)



## Examples of Evolutionary optimization Algorithm

- 1) Genetic algorithm (GA)
- 2) Bat algorithm (BA)
- 3) Artificial Bee colony (ABC)
- 4) Differential evolution (DE)
- 5) Ant colony optimization (ACO)
- 6) Particle swarm optimization (PSO)

## EXPloration & EXPlotation

	EXPloration	EXPlotation
Meaning	↳ Find new solutions in search domains which haven't been evaluated before.	↳ try to improve the current found solution by performing small changes that lead to new solutions.
Variation of Population members from one iteration to another	large	very small

### Basic element affect on EXPloration & EXPlotation

1) Population size (no. of members in Population) affects on EXPloration rate.

Large size of Population  $\Rightarrow$   $\uparrow\uparrow$  rate of EXPloration.

2) Control Parameters of optimization algorithm  
↳ affect on exploration and exploitation.

### Notes

\* optimization algorithm starts from larger exploration rate  
↳ this allows the algorithm to cover large regions of search domains quickly.

\* As iterations processes : exploration rate decreased  
↳ allows to exploit the promising regions that are previously explored.

### Benchmark Functions

↳ standard complex mathematical functions with different chls are used to test optimization algorithm "to evaluate efficiency & robustness"

How this test happens?

له بعد اختيار مجموعة ال (benchmark Functions) الخاضعة الى (Algorithm)   
 يبدأ ~~مع~~ مع الدوال دي بعد N من المرات ~~لا~~ <sup>(run)</sup> كل

على (run) بتحتوى على (no. of iterations)

له نتيجة الاختيار بتطلع رقم 1 او Successful runs for each  $P_n$ .

⇒ run is considered successful if algorithm reached the required global optimum.

## Common Benchmark Functions

Benchmark Functions	Search range	Functions Properties
Sphere Function	$f_1(x) = \sum_{i=1}^{D} x_i^2$	$[-100, 100]^D$ unimodal separable
Rosenbrock Function	$f_2(x) = \sum_{i=1}^{D-1} [100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2]$	$[-2.048, 2.048]$ unimodal ( $D < 4$ ) Multimodal ( $D \geq 4$ ) nonseparable
Ackley Function	$f_3(x) = 20 + e - 20 e^{-0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2}} - \frac{1}{e} \sum_{i=1}^D \cos(2\pi x_i)$	$[-30, 30]^D$ Multimodal nonseparable
Griewank Function	$f_4(x) = 1 + \sum_{i=1}^D \frac{x_i^2}{4000} - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right)$	$[-600, 600]^D$ Multimodal separable non- <del>sta</del>
Rastrigin Function	$f_5(x) = \sum_{i=1}^D [10 + x_i^2 - 10 \cos(2\pi x_i)]$	$[-5.12, 5.12]^D$ Multimodal separable
Schwefel Function	$f_6(x) = 418.9829 D - \sum_{i=1}^D x_i \sin(\sqrt{ x_i })$	$[-500, 500]^D$ Multimodal separable

Note that All of these Functions are  
 \* single-objective.      \* unconstrained